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CURRENT ACCOUNT SUSTAINABILITY IN BRAZIL: A NON-LINEAR APPROACH

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ABSTRACT/RÉSUMÉ

Current account sustainability in Brazil: A non-linear approach

The possibility that a country's external current account may adjust nonlinearly to shocks is attracting increasing attention in the empirical literature. To shed further light on this issue in the context of emerging-market economies, this paper uses Brazilian data to estimate the determinants of the current account in a smooth-transition vector-autoregressive (ST-VAR) setting. We allow for the transition parameters and the model coefficients to be estimated simultaneously by non-linear constrained maximum likelihood. We find strong evidence of non-linearity in the VAR when (lagged) government consumption and investment are used as the variables governing transition across regimes. The computation of non-linear impulse response functions suggests that the system's history, as well as the sign and magnitude of shocks, affect the current account's responses to exogenous changes in income, government consumption and investment. In particular, responses to fiscal shocks depend on whether they are positive or negative and whether they follow periods of fiscal expansions or contractions. Current account responses to a positive fiscal impulse are much stronger when conditioned on periods of fiscal expansion (rising government consumption) than retrenchment. The importance of conditioning history and the magnitude of shocks in the current account's response to shocks is confirmed by forecast error variance decomposition analysis.

JEL classification: C22; C32; F32
Key words: Brazil; current account; smooth-transition non-linear VAR; non-linear impulse response functions

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La soutenabilité du compte courant brésilien : une approche non-linéaire

La possibilité que le compte courant d'un pays puisse s'ajuster non-linéairement aux chocs suscite un intéret croissant dans la littérature empirique. Dans ce document, nous nous intéressons au cas des économies émergentes. Plus précisément, nous analysons, sur données brésiliennes, les déterminants du compte courant dans le cadre de modèles vectoriels autorégressifs à transition lisse (ST-VAR). Nous estimons simultanément les paramètres de transition et les coefficients du modèle par maximum de vraisemblance non-linéairement contraint. Nous démontrons l'existence de non-linéarité dans le VAR en utilisant les dépenses publiques (retardées) du gouvernement et l'investissement comme variables de transitions entre les différents régimes. Les fonctions de réponse suggèrent que la situation budgétaire initiale, ainsi que le signe et la magnitude du choc, jouent sur la réponse du compte courant aux variations non anticipées du revenu, des dépenses publiques et de l'investissement. En particulier, les réponses à un choc positif sur les dépenses publiques sont plus fortes en période d'expansion budgétaire (croissance des dépenses publiques) qu'en période de contraction. L'intérêt de prendre en compte la situation budgétaire et la magnitude des chocs dans la réponse du compte courant est confirmé par une décomposition de la variance de l'erreur de prévision.

JEL classification : C22 ; C32 ; F32
Mots-clés : Brésil ; compte courant ; modèles vectoriels autorégressifs à transition lisse ; fonctions de réponse non-linéaire

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Current account sustainability in Brazil: A non-linear approach

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1. Introduction

There is a growing literature on current account determination and sustainability in emerging-market economies. The rational expectations, intertemporal model of current account determination has become the workhorse of empirical analysis to take into account the effects of consumption smoothing on the saving-investment balance (Ghosh, 1995; Ghosh and Ostry, 1995). This methodology has also been used to gauge the extent of international capital mobility in industrial countries (Ghosh, 1995; Glick and Rogoff, 1995) and emerging-market economies (Hussein and de Mello, 1999). The intertemporal model predicts that the ratio of the current account balance to the national cash flow (*i.e.* GDP minus investment and government consumption) follows a stationary stochastic process with unconditional mean. Most of the empirical literature has so far assumed that adjustment to this unconditional mean is linear. Nevertheless, past episodes of current account reversals suggest that adjustment is not uncommon when current account imbalances become too "large" (Milesi-Ferretti and Razin, 1998; Chinn and Prasad, 2003; Freund, 2005; Freund and Warnock, 2005; Eichengreen and Adelet, 2005; Algieri and Bracke, 2007). Evidence in favour of such country-specific threshold effects, which is just one of the types of nonlinearity that may affect the current account dynamics, is provided by Clarida *et al.* (2006) for the G7 countries in a threshold autoregressive model. Arghyrou and Chortareas (2008) also test for nonlinear effects in the current account dynamics of the EMU (European Monetary Union) countries using a smooth-threshold error correction model.

To our knowledge, there has been no attempt to date to test for the presence of nonlinearity in the current account dynamics of emerging-market economies.[2] To shed further light on this issue, we use Brazilian data and a smooth-transition vector-autoregressive (ST-VAR) technique (Weise, 1999; Camacho, 2004) to model the current account. This methodology allows for transition across current

1. This paper was written as background material for the *OECD Economic Survey of Brazil*, published in July 2009 under the authority of the Secretary General of the OECD and discussed at the Economic and Development Review Committee (EDRC) on 4 June 2009. The authors are indebted to Melika Ben Salem for helpful comments and discussions but remain solely responsible for remaining errors or omissions. Special thanks are due to Anne Legendre for research assistance and Mee-Lan Frank for excellent technical assistance

2. Chortareas *et al.* (2004) test the hypothesis of current account sustainability in a sample of Latin American countries by assessing the unit root properties of the external debt-to-GDP ratio. They find evidence of nonlinearity on the basis of a self-exciting threshold autoregressive model.

account regimes to be driven by a function defined for a small set of parameters and whose form does not need to be imposed *a priori*. We select the best functional form of the transition function by implementing multivariate versions of standard non-linearity tests for different transition variables (*e.g.* Luukkonen, Saikkonen and Teräsvirta, 1988). We improve upon the existing literature (Weise, 1999) by allowing the transition parameters and the model coefficients to be estimated simultaneously by non-linear constrained maximum likelihood.

We then compute nonlinear impulse responses. In a linear setting, responses are symmetrical to positive and negative shocks and independent of the magnitude of shocks. However, if adjustment is nonlinear, the current account dynamics depend not only on the sign and magnitude of shocks, but also on the system's conditioning history. This is important from the policymaking viewpoint, because the potency of counter-cyclical fiscal impulses depends on how much of the impulse leaks through the external current account. In a nonlinear setting, the current account responds to a fiscal impulse in a manner that depends in turn on the size and magnitude of the impulse and on whether fiscal policy had been contractionary or expansionary.

Our main findings are as follows. *First*, linearity can be rejected against an exponential smooth-transition alternative when (one-period) lagged investment and government consumption are used as the variables governing transition across current-account regimes. The fit of the non-linear VARs estimated for both transition variables is good overall.

Second, we use the estimated non-linear VAR parameters to compute generalised impulse response functions (GIRFs) conditioned on the system's different histories (past periods of rising or falling investments/government consumption). When investment is used as the transition variable, current account responses do not appear to be affected by conditioning histories. However, when government consumption is used as the transition variable, responses to a *positive* fiscal shock are much stronger in the short run when conditioned on periods of rising government consumption. Responses to *negative* fiscal shocks do not seem to differ across conditioning regimes. This implies that the magnitude and the size of current account adjustments to a fiscal shock depend on past fiscal outcomes.

Third, forecast error variance decomposition analysis shows that current account shocks explain most of the fluctuations in the current account balance, although income and investment shocks also play an important part, regardless of the transition variable used. In addition, the share of current account dynamics explained by expenditure shocks depends essentially on the conditioning histories and the size of shocks.

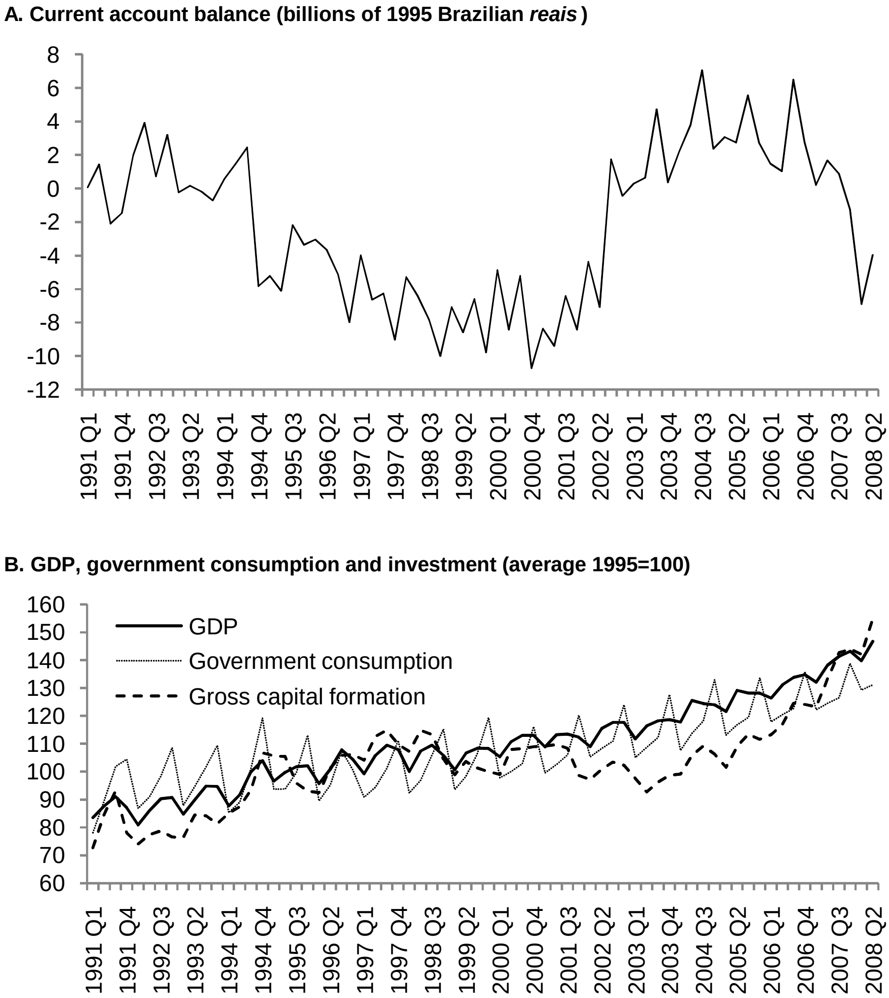
The paper is organised as follows. In Section 2, we describe the data, test for non-stationarity in the series and for the presence of non-linearity in a smooth-transition VAR framework, and estimate both linear and non-linear VARs. Section 3 reports the results of the impulse response analysis carried out for the non-linear system. Section 4 reports the forecast error variance decomposition results. Section 5 concludes.

2. Data and empirical model

The data

We model the current account balance (*CA*) as a function of GDP (*Y*), gross capital formation (*I*) and government consumption (*G*). Quarterly data from 1991:1 to 2008:2 are available from the Central Bank of Brazil. The current account is measured in millions of *reais* of 1995 (USD values are converted into *reais* using the period-average exchange rate and then deflated by the GDP deflator), while the cash-flow components are defined as (chain-linked) indices with base average 1995=100.[3] On the basis of the raw (seasonally unadjusted) data (Figure 1), it appears that the current account balance has fluctuated between a quarterly surplus of about 7 billion *reais* in 2004Q3 (4.9% of national cash flow) and a deficit of 10.7 billion *reais* in 2000Q4 (8.5% of national cash flow).

Figure 1. **Current account balance, GDP, government consumption and investment, 1991:1 to 2008:2**



Source: Central Bank of Brazil.

For the purpose of the estimations reported below, all variables were pre-filtered to remove seasonal effects by regressing them on a constant and (centered) seasonal dummies. A visual inspection of the series suggests that the current account balance may suffer from multiple breaks in means. We tested this

3. This is because the current account balance can be negative, which would make it impossible to use a double-log specification. Preliminary estimations also show that the definition of the cash-flow components as indices improves the maximum likelihood estimates.

hypothesis by implementing the Bai and Perron (1998; 2003) procedure.[4] The results (not reported) suggest the presence of three breaks: the third quarter of 1994, a period that followed the implementation of a macroeconomic adjustment program (the Real Plan) and monetary reform; the second quarter of 2002, when a confidence crisis erupted in the run-up to a presidential election later in the year; and the second quarter of 2006. The current account series was therefore pre-filtered again to remove the mean breaks.

To test for the presence of unit roots in the data, we used the Phillips-Perron, the Elliott-Rothenberg-Stock and the GLS Augmented Dickey-Fuller tests (Ng and Perron, 2001; Perron and Qu, 2007). The results, reported in Table 1, suggest that the current account balance is stationary in levels, while GDP, investment and government spending are difference-stationary. Since our objective is to estimate a smooth-transition multivariate model, we need to account for the possibility of univariate non-linearity in unit root testing. Kapetanios, Shin and Snell (2003, henceforth KSS) show that the standard ADF test has no power against the alternative of a non-linear but globally stationary STAR process. To overcome this problem, they propose a simple modification to the ADF test as follows:

$$\Delta y_t = \delta y_{t-1}^3 + \sum_{j=1}^{p} \rho_j \Delta y_{t-j} + \varepsilon_t \tag{1}$$

We applied this test to the non-stationary (demeaned and detrended) variables, as suggested by KSS, starting with a maximum of 6 lags and selecting the optimal lag length p according to the SBC criterion. The test results (0.92 for GDP, -1.07 for investment and -0.91 for government spending, for a 5% critical value for the modified demeaned and detrended ADF test of -2.93) confirm the findings reported in Table 1: the non-linear globally stationarity hypothesis is rejected for GDP, investment and government spending. These variables were therefore first-differenced prior to the estimation of the VAR.

Table 1. **Unit root tests**[1]

	ADF^{GLS}	5% confidence level	MZ_t^{GLS}	5% confidence level	MP_t^{GLS}	5% confidence level
CA_t	-3.13*	-1.98	-2.55*	-1.98	1.89*	3.17
Y_t	-0.53	-2.91	-0.36	-2.91	33.48	5.48
I_t	-1.31	-2.91	-1.48	-2.91	14.61	5.48
G_t	-1.05	-2.91	-0.49	-2.91	38.28	5.48

1. ADF^{GLS}, MZ_t^{GLS} and MP_t^{GLS} refer respectively to the GLS augmented Dickey-Fuller test, the modified Phillips-Perron *t*-test and the modified Elliott-Rothenberg-Stock point optimal test. The auxiliary regressions for Y_t, I_t and G_t include a linear trend. The modified AIC criterion was used to set the optimal number of lags for the computation of the autoregressive spectral density function. (*) denotes significance at the 5% level.

Source: Authors' estimations.

Testing for non-linearity

We tested the hypothesis of linearity in the multivariate VAR against the alternative of a smooth-transition vector system (ST-VAR). The testing strategy follows the selection scheme proposed by Camacho (2004). To do so, we first estimated the linear VAR and selected the optimal lag-order (p) based on the Schwartz information criterion. We then applied the linearity tests to the baseline VAR augmented by the non-linear term. We followed Luukkonen, Saikkonen and Teräsvirta (1988) and Granger and

4. Break dates were estimated by the sequential method and checked through the repartition procedure at the 1% significance level.

Teräsvirta (1993) in approximating the smooth-transition function by a Taylor expansion around $\gamma = 0$ (the slope parameter of the transition function defined below). We also assumed that the transition variable (*s*) belongs to the set of regressors (the lagged endogenous variables).[5]

The unrestricted model can be estimated as follows. Consider a restricted *k*-dimensional linear VAR(*p*), with vectors of time series $X_t = (x_{1,t}, \ldots, x_{k,t})'$ and residuals $(\hat{u}_t^r)$, and covariance matrix Ω_r. The unrestricted model is obtained by regressing either $\hat{u}_t^r$ or X_t on an augmented auxiliary regression, which includes cross-products of powers one, two and three of the selected transition variable (s_{t-d}) with the set of lagged regressors:

$$X_t = \mu + \sum_{i=0}^{3} \sum_{j=1}^{p} \Phi_{i,j} X_{t-j} s_{t-d}^i + v_t \qquad (2)$$

We used a likelihood ratio (*LR*) test to test the hypothesis of linearity (Weise, 1999; Camacho, 2004).[6] To do so, let $\hat{v}_t^{ur}$ be the vector of estimated residuals from the unrestricted regression (2) and Ω_{ur} the covariance matrix. The linearity hypothesis can be tested through the *LR* statistic, $LR = T(\log|\Omega_r| - \log|\Omega_{ur}|)$, which is asymptotically distributed as a χ^2 with (*p*+1) degrees of freedom.

We took all lagged endogenous variables as potential switching variables. Whenever the null hypothesis of linearity can be rejected for a specific transition variable $s_{t-d} = x_{k,t-j}$, where *d* is the delay parameter, the problem of choosing between either an exponential or a logistic transition function arises. This can be dealt with by implementing a sequential testing approach, based on testing a sequence of nested null hypotheses in equation (2) (Granger and Teräsvirta, 1993; Teräsvirta, 1994; Camacho, 2004). As for the linearity test, three *LR* test statistics are computed for each non-linear candidate model. The first one is a test of the exponential STR model against the logistic STR model (*i.e.*, $H_{01}: \Phi_{i,3} = 0$ against $H_{11}: \Phi_{i,3} \neq 0$). Since $\Phi_{i,2}$ cannot be equal to 0 if the true model is exponential, but it can be equal to 0 if the true model is logistic, a second suitable test involves the following null and alternative hypotheses: $H_{02}: \Phi_{i,2} = 0 \,|\, \Phi_{i,3} = 0$ against $H_{12}: \Phi_{i,2} \neq 0 \,|\, \Phi_{i,3} = 0$. Rejection of the null is not informative, if taken alone. Thus, a final test can be defined as $H_{03}: \Phi_{i,1} = 0 \,|\, \Phi_{i,2} = \Phi_{i,3} = 0$, against $H_{13}: \Phi_{i,1} \neq 0 \,|\, \Phi_{i,2} = \Phi_{i,3} = 0$.[7] All these *LR* statistics are asymptotically distributed as a χ^2 with 2(*p*+1) degrees of freedom. The tests can be interpreted as follows. Rejection of the first null hypothesis implies that a logistic model is preferred. When the null cannot be rejected by tests 1 and 3, but can be rejected by test 2, the exponential model is preferred. When the null cannot be rejected by tests 1 and 2, but can be rejected by test 3, the logistic model is preferred.

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5. A transition variable not belonging to the set of regressors must be treated either as an exogenous variable, such as a time-varying transition variable, or as a function of endogenous variables. See Camacho (2004) for more information.

6. See Tsay (1986), Luukkonen *et al.* (1988) and Saikkonen and Luukkonen (1988) for further discussion on linearity tests.

7. As for the linearity test, model selection is carried out by substituting the non-linear function by a suitable Taylor expansion. The logistic function can be approximated by a third-order Taylor approximation, while a second-order expansion would be sufficient to approximate the exponential function (Luukkonen *et al*., 1988; Saikkonen and Luukkonen, 1988).

The linear VAR was estimated for up to 4 lags. Based on the SBC criterion, the lag length used to estimate the linear VAR and to compute the likelihood value for the linear benchmark was set to 2.[8] The non-linear alternative was estimated following the procedure described above. The results of the linearity tests and the model selection statistics are reported in Table 2. The linearity tests suggest the rejection of the null of linearity at the 5 and 1% levels against smooth-transition alternatives involving ΔI_{t-1} and ΔG_{t-1} as the transition variables. We therefore focused on these two variables to interpret the results of the model selection tests. Tests 1 and 3 failed to reject their null hypotheses, while we could strongly reject the null hypotheses specified in test 2. These results suggest that an exponential smooth-transition function might better fit the non-linear component of the VAR.

Table 2. **Linearity and model selection tests**

Switching variable	Linearity test		Model selection tests					
			Test 1		Test 2		Test 3	
	Statistic	*p*-value[1]	Statistic	*p*-value[1]	Statistic	*p*-value[1]	Statistic	*p*-value[1]
CA_{t-1}	66.49	0.7892	27.30	0.8829	31.44	0.7026	23.01	0.2992
CA_{t-2}	73.15	0.5763	46.15	0.2045	30.54	0.7367	15.02	0.8566
ΔY_{t-1}	92.89	0.0815	38.14	0.4650	62.56	0.0101	19.48	0.5532
ΔY_{t-2}	91.42	0.0956	42.79	0.3061	50.27	0.0829	22.59	0.3145
ΔI_{t-1}	97.10	0.0433	44.47	0.2414	59.87	0.0172	20.39	0.4732
ΔI_{t-2}	85.27	0.2099	38.97	0.4511	44.74	0.2002	23.31	0.2796
ΔG_{t-1}	121.97	0.0003	51.86	0.0915	85.39	0.0001	21.92	0.3637
ΔG_{t-2}	88.61	0.1381	35.51	0.5822	45.42	0.1806	28.97	0.0668

1. The bootstrapped *p*-values are computed by randomly drawing (with replacement) from the distribution of linear VAR residuals and constructing 10 000 artificial datasets.

Source: Authors' estimations.

Estimating the ST-VAR

The selected non-linear models are the exponential ST-VAR(2), with either ΔI_{t-1} or ΔG_{t-1} as the transition variables. We estimated the model by maximum likelihood. Unlike Teräsvirta and Anderson (1992) and Weise (1999), we did not impose arbitrary restrictions on the linear or non-linear coefficients and let the system converge to the set of optimal parameters. We only required all VAR equations to have the same transition function. In addition, given the large number of parameters and the limited set of observations, we allowed the constant to shift across regimes, while leaving the remaining parameters unchanged. In doing so, we focused on mean adjustments in the current account balance in response to shocks.[9]

The ST-VAR can be defined as:

$$X_t = \mu + \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \theta F(\gamma, c, s_{t-d}) + \varepsilon_t \tag{3}$$

8. The information criterion for the linear VAR(2) was 7.89, while higher values (8.05, 8.18 and 8.83) were obtained for the competing models (with one, three and four lags, respectively).

9. The modified ADF test results support this choice. Rejection of the non-linear STAR alternative suggests that non-linear adjustment does not take place in the stochastic part of the model, but rather in the deterministic part. This allows us to set a mean regime framework, where the (smooth) adjustment defines a time-conditional segmented equilibrium of the current account with the national cash-flow components.

where $X_t = (CA_t, \Delta Y_t, \Delta I_t, \Delta G_t)'$ is the vector of variables entering the VAR, μ is a vector of constants, Φ_p are the vector autoregressive parameters, θ is a vector of non-linear parameters, and ε_t is a vector of residuals.

The exponential (smooth-transition) function is defined as:

$$F(\gamma, c, s_{t-d}) = \left(1 - \exp\left\{-\left(\frac{\gamma}{\sigma_s^2}\right) \times \left[s_{t-d} - c\right]^2\right\}\right) \quad (4)$$

where γ is the slope parameter (scaled by the variance of the transition variable, as suggested by Granger and Teräsvirta, 1993), which defines the degree of smoothness of the transition function across regimes; *c* is the threshold parameter; and $s_{t-d} = (\Delta I_{t-1}; \Delta G_{t-1})$ is the switching variable.

The VARs were estimated by maximum likelihood using the Newton-Raphson optimisation algorithm. Initial values for the non-linear parameters (γ and *c*) were estimated through a grid search procedure, using the values that minimised the determinant of the variance-covariance matrix of the residuals obtained from preliminary OLS estimates of the non-linear VAR. Linear constraints were imposed on the non-linear parameters in order to obtain economically interpretable results: γ was set to be non-negative and the range of actual values for *c* was restricted to lie between the minimum and the maximum values of the transition variable, with a small trimming of 2.5% at the beginning and the end of the sample.

Table 3 reports the maximum likelihood estimations. The smoothness parameters for the two ST-VAR models are quite low (0.86 and 2.31, respectively, when investment and government consumption are used as the transition variables), suggesting a slow transition across regimes. On the other hand, the estimated thresholds have opposite signs: in model 1 $(s_{t-d} = \Delta I_{t-1})$, the turning point is -9.8% of (lagged) changes in investment, while in model 2 $(s_{t-d} = \Delta G_{t-1})$ the threshold is positive, at 2.4% of (lagged) changes in government spending.

Table 3. **Smoothness and threshold parameter estimates**

Transition variable	Non-linear parameter	Grid search	Maximum likelihood estimates
ΔI_{t-1}	γ	1.000	0.857
	c	-9.713	-9.807
ΔG_{t-1}	γ	1.009	2.311
	c	2.244	2.403

Source: Authors' estimations.

The results of the specification tests for the non-linear VAR are reported in **Table 4**. We tested for serial correlation in the residuals and the general fit of the model.[10] The results suggest the presence of some serial correlation at lags 2 up to 4. The relative mean squared errors suggest that the non-linear

10. This is an extension to the multiple equation framework of the standard test of serial independence of errors (Camacho, 2004) proposed by Eitrheim and Teräsvirta (1996). The LM statistic is distributed as a χ^2 with 4*r* degrees of freedom.

models have marginally better fits (0.88 and 0.98, respectively, for models 1 and 2) when compared to the linear specification.[11]

Table 4. **Exponential ST-VAR model: Serial correlation tests**

Test[1]	ΔI_{t-1}	ΔG_{t-1}
SI(1)	10.34 [0.04]	8.99 [0.06]
SI(2)	16.28 [0.04]	17.69 [0.03]
SI(3)	35.65 [0.00]	35.40 [0.00]
SI(4)	44.27 [0.00]	46.48 [0.00]
Relative MSE	0.8841	0.9784

1. SI(r) is the test for serial independence of the residuals at the r-th lag. Asymptotic *p*-values are reported in brackets.

Source: Authors' estimations.

3. Symmetric and asymmetric shocks: Impulse-response analysis

We used the parameter estimates obtained from the non-linear ST-VAR to gauge the effects of asymmetric shocks to income, investment and government consumption on the current account balance. The estimation of impulse response functions is straightforward in linear VARs, but not in a non-linear setting, where these functions are sensitive to initial conditions and the magnitude of shocks. In a linear (symmetric) framework, impulse response functions can be computed as the impact of a one-standard-deviation increase in the *j*-th variable on the *i*-th variable in the VAR, for each time unit *t*+*h*. Following Koop *et al.* (1996), a traditional impulse response function can be written as:

$$IRF_X(h,\delta,\omega_{t-1}) = \begin{array}{l} \mathrm{E}\left[X_{t+h}\middle|\varepsilon_t=\delta,\varepsilon_{t+1}=0,\ldots,\varepsilon_{t+h}=0,\omega_{t-1}\right] \\ -\mathrm{E}\left[X_{t+h}\middle|\varepsilon_t=0,\varepsilon_{t+1}=0,\ldots,\varepsilon_{t+h}=0,\omega_{t-1}\right] \end{array} \tag{5}$$

for $h=1,2,3,\ldots$.

The standard representation of the impulse response functions for linear models can be interpreted as "… the difference between two different realisations of X_{t+h} that are identical up to $t-1$. One realisation assumes that between *t* and $t+h$ the system is hit only by a shock of size δ at period *t* (*i.e.* $\varepsilon_t=\delta$), while the second realisation, taken as the benchmark, assumes that the system is not hit by any shocks between *t* and $t+h$" (Koop *et al.*, 1996, p. 122). However, since non-linear models are asymmetric, the impulse response functions depend on initial conditions; they are not invariant to past history (ω_{t-1}), as in the linear case. This is because non-linear functions have mapping properties that are strictly related to the initial

11. The MSEs for the non-linear models are 1.69 and 1.87, when investment and government consumption are used as transition variables, respectively, and 1.91 for the linear model.

parameterisation. In addition, the future pattern of the system after the shock is crucial for the computation of non-linear response functions. This is due to the fact that a shock at time *t* not only has an effect on the actual value of the *i*-th variable, but it can also push the system from a regime into another and thus modify the dynamic response at $t+1$, and so on. In the linear framework, future shocks are usually set to zero for convenience, because the expectation of the path of X after a shock, conditional on future shocks, is equal to the path of the variable when future shocks are set to their expected values (Huang *et al.*, 2008). But this is not the case in the asymmetric framework, where shocks cannot be set to zero, although they can be treated as random realisations from the same stochastic process that generated $\{X_t\}$.

Against this background, impulse response functions can be computed in a non-linear framework by conditioning the path of X on a particular history ω_{t-1}, drawing (with replacement) from the distribution of the non-linear model's residuals in order to generate a random sequence of shocks, and then computing the generalised impulse response functions, GIRF (Koop *et al.*, 1996):

$$GIRF_X(h, \delta, \omega_{t-1}) = \mathrm{E}\left[X_{t+h} \middle| \varepsilon_t = \delta, \omega_{t-1}\right] - \mathrm{E}\left[X_{t+h} \middle| \omega_{t-1}\right] \tag{6}$$

We followed Weise (1999) in constructing the distribution of the GIRFs and computed *n* bootstrapped replications of this process by simulating the evolution of both the shocked and the benchmark realisations of X_{t+h}. Finally, mean and median impulse responses were computed.[12] Shocks were identified on the basis of a Cholesky decomposition of the residuals obtained from the linear model, where government consumption was the last series to enter the VAR. In doing so, we set the transmission of shocks in a standard fashion, according to which changes in fiscal policy (measured by government consumption) affect investment and the level of GDP. The current account balance enters the VAR first. The size of the shocks was set, alternatively, at one and two standard deviations.

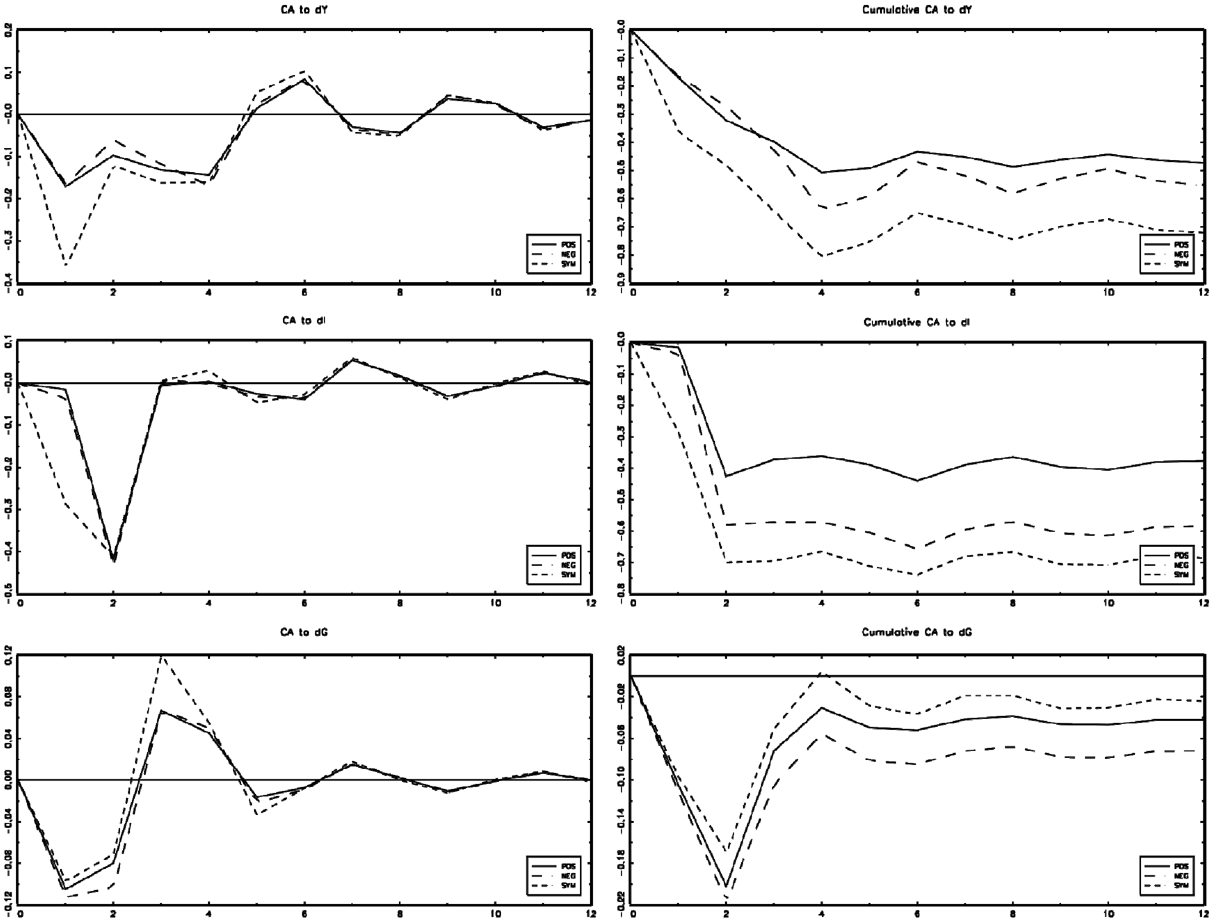
We conditioned the expected path of future realisations of the current account balance on four particular histories ω_{t-1}: periods of rising capital formation $(\Delta I_{t-1} > 0)$ (Figures 2 and 6), periods of falling capital formation $(\Delta I_{t-1} < 0)$ (Figures 3 and 7), periods of rising government spending $(\Delta G_{t-1} > 0)$ (Figures 4 and 8) and periods of falling government spending $(\Delta G_{t-1} < 0)$ (Figures 5 and 9). The figures depict the estimated GIRFs (left panels) and cumulative responses (right panels) of the current account to a one-time shock to GDP, investment and government spending (shown in the top, middle and bottom panels, respectively). Current account responses to positive (negative) shocks are plotted in solid (dashed) lines. Standard symmetric responses are also plotted for comparison in short-dashed lines. The number of bootstrap replications was set to 5 000. As suggested by Weise (1999), the presence of outliers can distort the distribution of GIRFs; as a result, we computed the median, rather than the average, responses to shocks.

The asymmetric impulse responses computed when investment is used as the transition variable (Figures 2-3 and 6-7) suggest that the non-linear model is fairly robust to the different histories under consideration (periods of rising or falling investment). Also, positive and negative shocks produce similar responses in magnitude: a positive (negative) shock to either investment or GDP has a negative (positive) net effect on the current account up to the second and fourth quarters following a shock, with a cumulative magnitude of 0.4 and 0.5 billion *reais*, respectively. Instead, a shock to government consumption has a small cumulative effect of around 0.04 billion *reais* one year after the shock. Finally, the symmetric model in general yields stronger current account responses to one-time shocks. When two standard-deviation shocks are considered, the asymmetric dynamic responses to negative shocks tend to coincide with the responses generated by the symmetric model, while the path of responses is robust to positive shocks.

12. For more details on the GIRF algorithm, see Weise (1999).

The asymmetric impulse responses computed when government consumption is used as the transition variable (Figures 4-5 and 8-9) show that a positive (negative) shock typically results in a negative (positive) current account response. In particular, a shock to either investment or GDP leads to a cumulative adjustment in the current account balance of about 0.7 billion *reais* up to two quarters following the shock. However, the dynamic responses are sensitive to the histories used to condition the system. In particular, responses to a positive fiscal (government consumption) shock are much weaker when conditioned on periods of falling government consumption (-0.04 billion *reais*) than on periods of rising government consumption (-0.25 billion *reais*) over two quarters following the shock. But responses to negative fiscal shocks are comparable when conditioned on periods of fiscal expansion and retrenchment. When two standard-deviation shocks are considered, the current account response to a positive fiscal shock is stronger, positively-signed and more frontloaded when conditioned on periods of fiscal expansions.

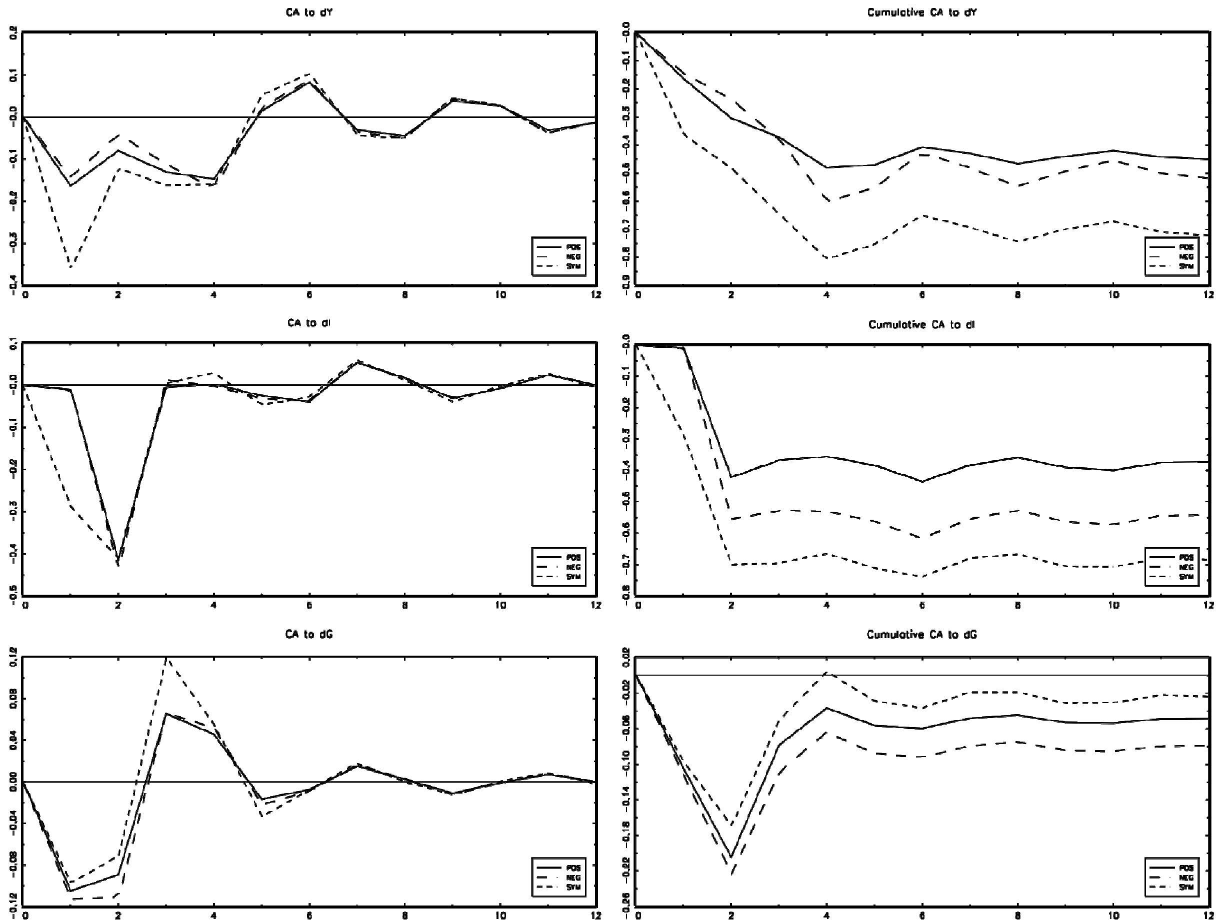
Figure 2. **Responses of *CA* to one standard-deviation shock** $(\omega_{t-1} : \Delta I_{t-1} > 0)$[1]



1. The charts refer to the case where $s_{t-d} = \Delta I_{t-1}$. The estimated GIRFs are shown on the left charts and the cumulative responses on the right. The dynamic responses of the current account to shocks to GDP, investment and government spending are shown in the top, middle and bottom panels, respectively. The solid (dashed) lines depict current account responses to positive (negative) shocks. Standard symmetric responses are plotted for comparison in short-dashed lines.

Source: Authors' estimations.

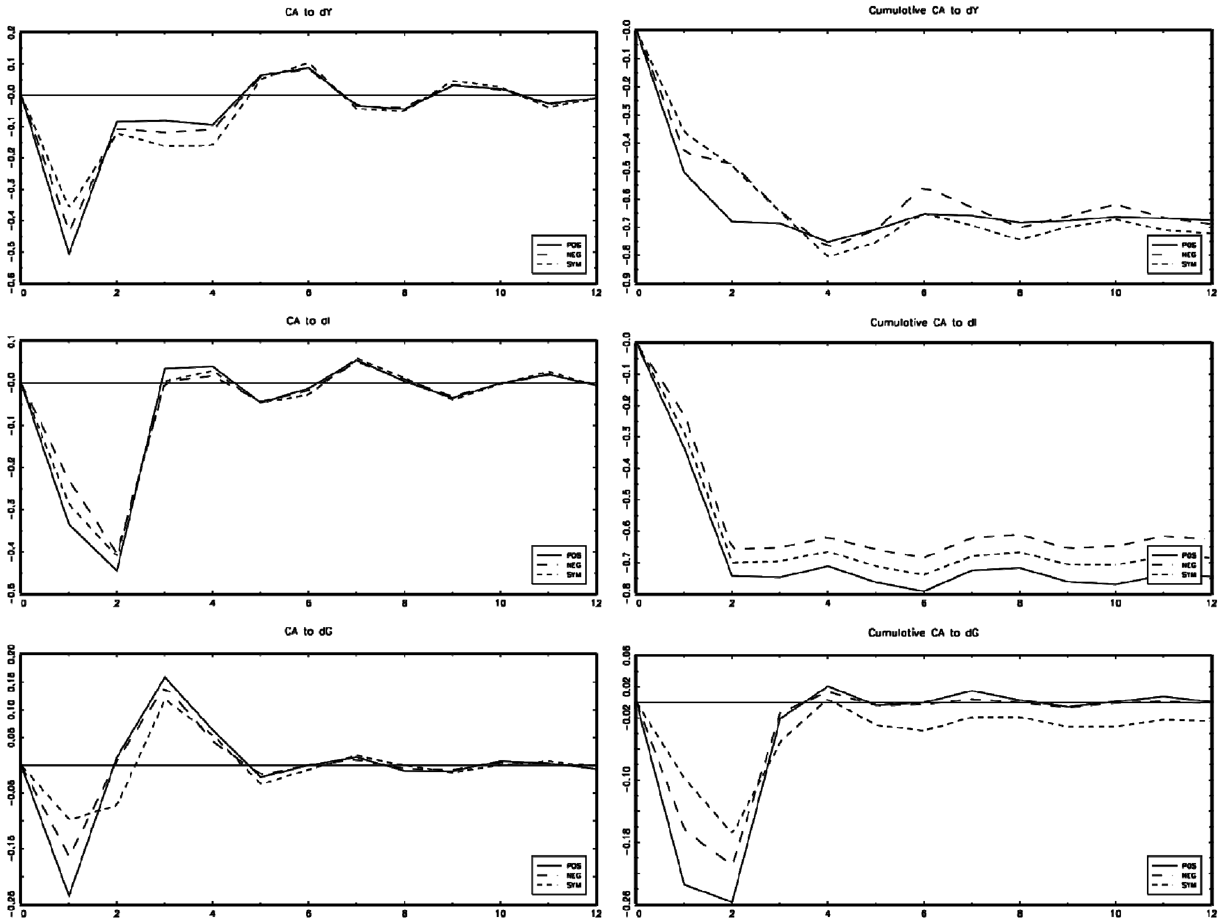
Figure 3. **Responses of *CA* to one standard-deviation shock** $(\omega_{t-1} : \Delta I_{t-1} < 0)$[1]



1. The charts refer to the case where $s_{t-d} = \Delta I_{t-1}$. The estimated GIRFs are shown on the left charts and the cumulative responses on the right. The dynamic responses of the current account to shocks to GDP, investment and government spending are shown in the top, middle and bottom panels, respectively. The solid (dashed) lines depict current account responses to positive (negative) shocks. Standard symmetric responses are plotted for comparison in short-dashed lines.

Source: Authors' estimations.

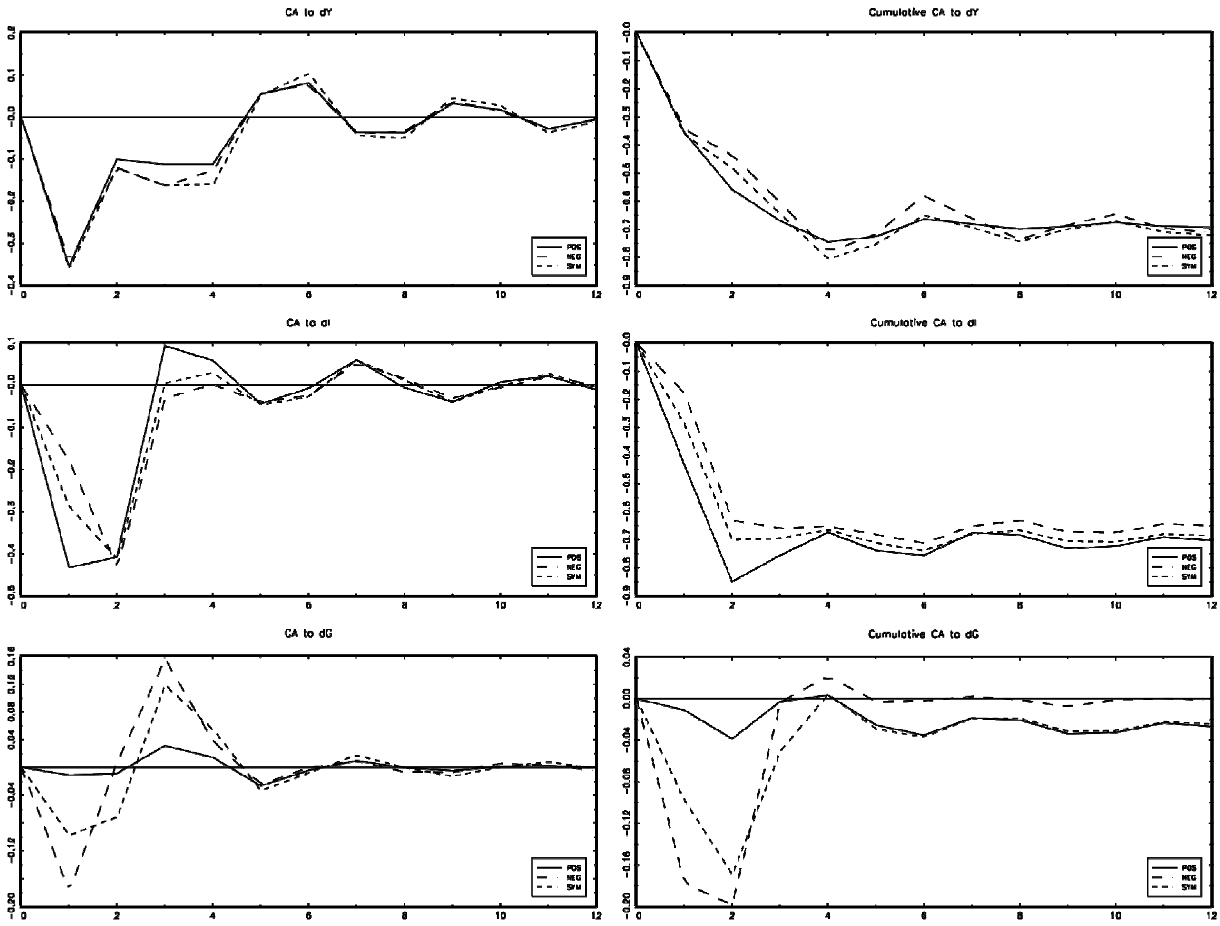
Figure 4. **Responses of *CA* to one standard-deviation shock** $(\omega_{t-1} : \Delta G_{t-1} > 0)$[1]



1. The charts refer to the case where $s_{t-d} = \Delta G_{t-1}$. The estimated GIRFs are shown on the left charts and the cumulative responses on the right. The dynamic responses of the current account to shocks to GDP, investment and government spending are shown in the top, middle and bottom panels, respectively. The solid (dashed) lines depict current account responses to positive (negative) shocks. Standard symmetric responses are plotted for comparison in short-dashed lines.

Source: Authors' estimations.

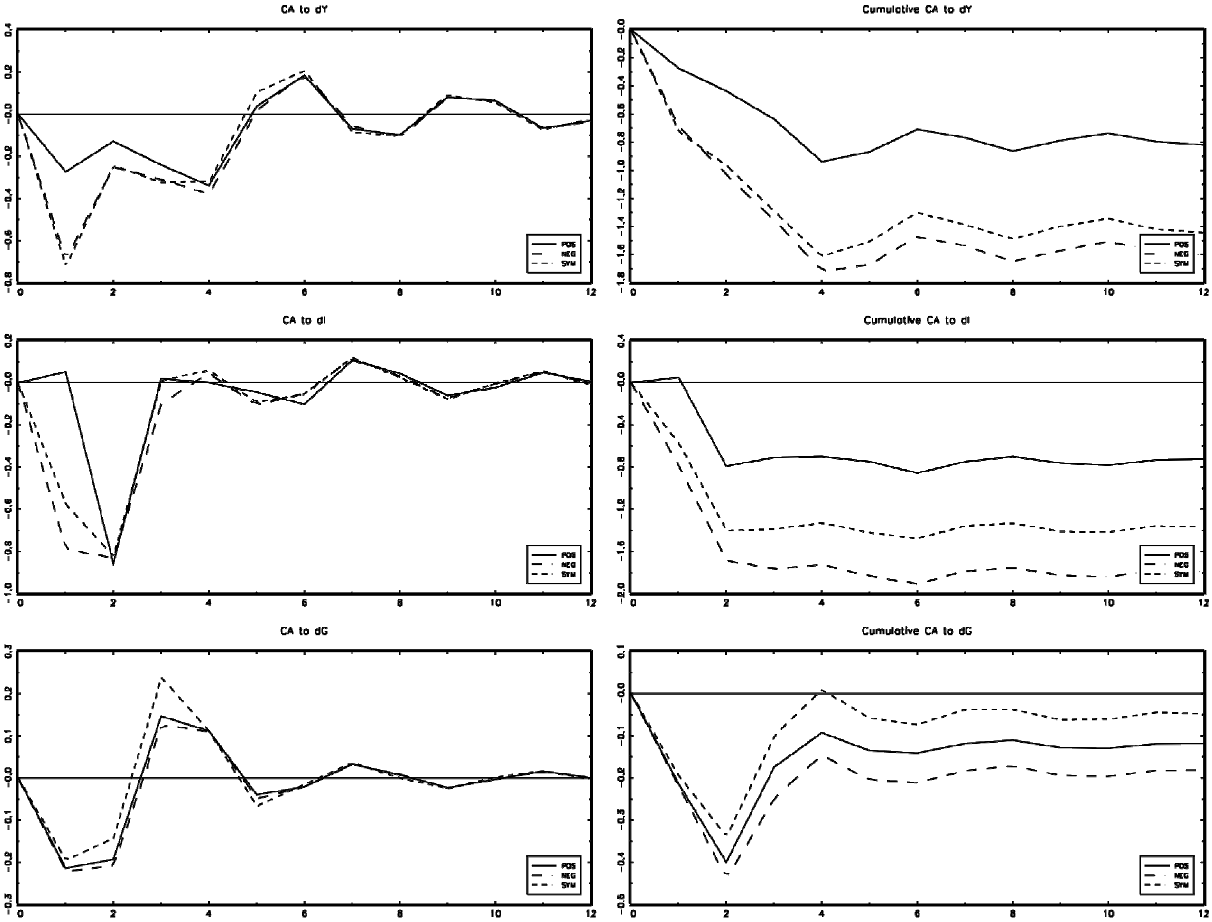
Figure 5. **Responses of *CA* to one standard-deviation shock** $(\omega_{t-1} : \Delta G_{t-1} < 0)$[1]



1. The charts refer to the case where $s_{t-d} = \Delta G_{t-1}$. The estimated GIRFs are shown on the left charts and the cumulative responses on the right. The dynamic responses of the current account to shocks to GDP, investment and government spending are shown in the top, middle and bottom panels, respectively. The solid (dashed) lines depict current account responses to positive (negative) shocks. Standard symmetric responses are plotted for comparison in short-dashed lines.

Source: Authors' estimations.

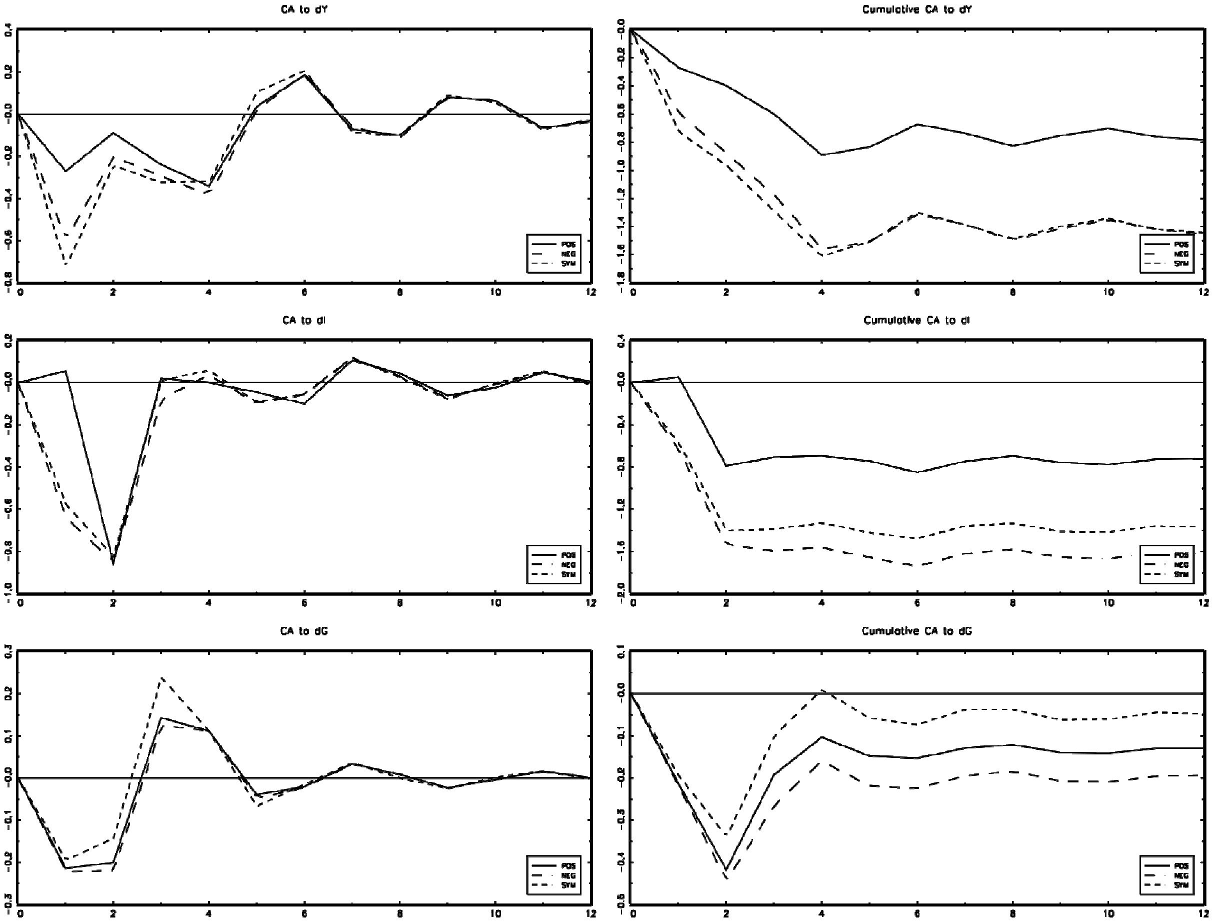
Figure 6. **Responses of *CA* to two standard-deviation shock** $(\omega_{t-1} : \Delta I_{t-1} > 0)$[1]



1. The charts refer to the case where $s_{t-d} = \Delta I_{t-1}$. The estimated GIRFs are shown on the left charts and the cumulative responses on the right. The dynamic responses of the current account to shocks to GDP, investment and government spending are shown in the top, middle and bottom panels, respectively. The solid (dashed) lines depict current account responses to positive (negative) shocks. Standard symmetric responses are plotted for comparison in short-dashed lines.

Source: Authors' estimations.

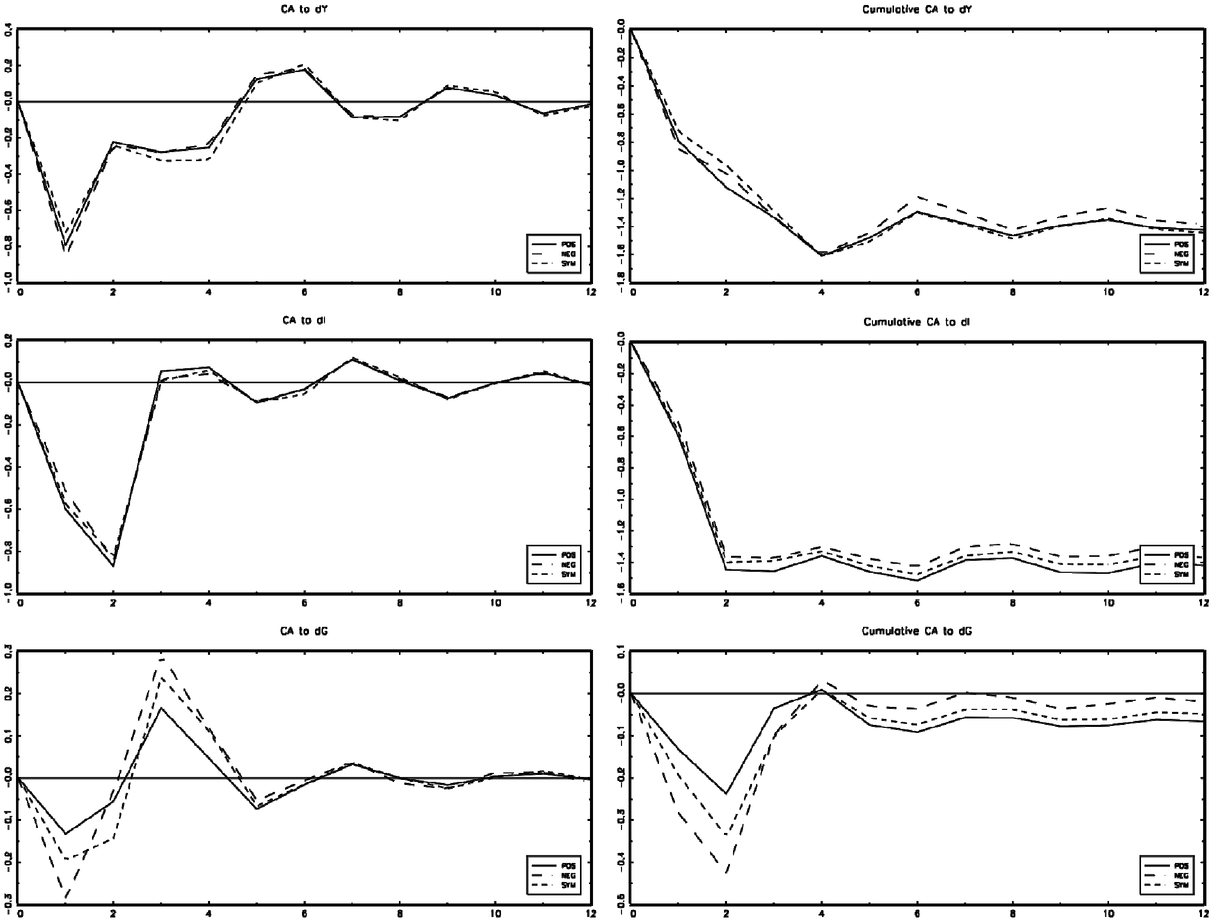
Figure 7. **Responses of *CA* to two standard-deviation shock** $(\omega_{t-1} : \Delta I_{t-1} < 0)$[1]



1. The charts refer to the case where $s_{t-d} = \Delta I_{t-1}$. The estimated GIRFs are shown on the left charts and the cumulative responses on the right. The dynamic responses of the current account to shocks to GDP, investment and government spending are shown in the top, middle and bottom panels, respectively. The solid (dashed) lines depict current account responses to positive (negative) shocks. Standard symmetric responses are plotted for comparison in short-dashed lines.

Source: Authors' estimations.

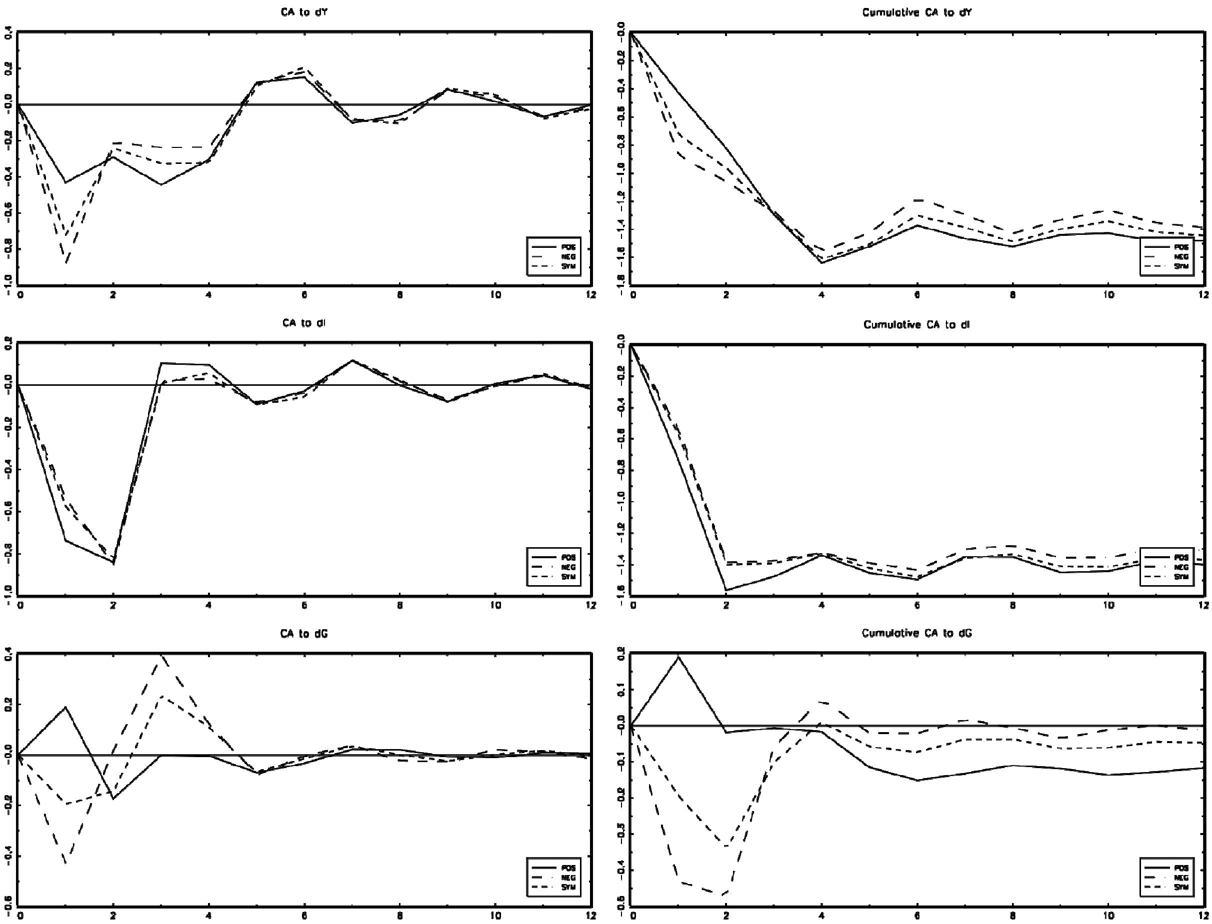
Figure 8. **Responses of *CA* to two standard-deviation shock** $(\omega_{t-1} : \Delta G_{t-1} > 0)$[1]



1. The charts refer to the case where $s_{t-d} = \Delta G_{t-1}$. The estimated GIRFs are shown on the left charts and the cumulative responses on the right. The dynamic responses of the current account to shocks to GDP, investment and government spending are shown in the top, middle and bottom panels, respectively. The solid (dashed) lines depict current account responses to positive (negative) shocks. Standard symmetric responses are plotted for comparison in short-dashed lines.

Source: Authors' estimations.

Figure 9. **Response of *CA* to two standard-deviation shock** $(\omega_{t-1}:\Delta G_{t-1}<0)$[1]



1. The charts refer to the case where $s_{t-d}=\Delta G_{t-1}$. The estimated GIRFs are shown on the left charts and the cumulative responses on the right. The dynamic responses of the current account to shocks to GDP, investment and government spending are shown in the top, middle and bottom panels, respectively. The solid (dashed) lines depict current account responses to positive (negative) shocks. Standard symmetric responses are plotted for comparison in short-dashed lines.

Source: Authors' estimations.

4. Forecast error variance decomposition

We finally computed the *n*-period forecast error variance of the $\{CA_t\}$ sequence. Using the GIRFs computed above, we estimated the proportion of fluctuations in the current account balance that can be explained by its own shocks, rather than shocks to the components of the national cash flow. The results are reported in Table 5 for the symmetric model, which is used as a benchmark for the non-linear specifications reported in Tables 6-13.

In the linear setting, fluctuations in the current account balance are explained predominantly by shocks to the current account. The results from the non-linear models are nevertheless quite different. In the case of models using investment as the transition variable, the decomposition patterns shown in Tables 6-7 and 10-11 (for two standard-deviation shocks), conditioned to the two histories, suggest that 90% of fluctuations in the current account can be explained by current account shocks, regardless of the conditioning history used. Investment shocks account for a larger share of fluctuations in the current account than income or government consumption shocks. Finally, the current account balance is more responsive to negative shocks than to positive shocks.

The results for the asymmetric models based on government consumption as the transition variable are reported in Tables 8-9 and 12-13 (for two-standard-deviation shocks). Current account shocks explain a lower share of fluctuations in the current account balance than when investment is used as the transition variable, regardless of conditioning history. Fiscal shocks play a modest role when the conditioning history is one of falling government consumption.

5. Conclusion

This paper used Brazilian data to estimate the determinants of the external current account in a smooth-transition vector-autoregressive (ST-VAR) setting. The baseline model is a VAR in the level of the current account balance and first-differences of GDP, investment and government consumption. The data set spans the period 1991:1 through 2008:2. The hypothesis of non-linearity was tested in the tradition of Luukkonen, Saikkonen and Teräsvirta (1988) and Granger and Teräsvirta (1993). Two exponential smooth-transition models were estimated using investment and government consumption as the transition variables. The transition parameters and the model coefficients were estimated simultaneously by non-linear constrained maximum likelihood. The non-linear ST-VAR parameters were used to study the dynamic responses of the current account balance to asymmetric income, investment and government consumption shocks, as well as for decomposing the variance of forecast errors. Since asymmetric impulse response and variance decomposition outcomes are sensitive to past histories and the sign and magnitude of shocks, we conditioned the system to histories of rising and falling investment and government consumption and compared the results for two different magnitudes of positive and negative shocks.

We find strong evidence of non-linearity in the VAR when (lagged) government consumption and investment are used as the transition variables. The computation of non-linear impulse response functions suggests that current account responses to income, investment and fiscal shocks are not overly sensitive to conditioning histories and the sign of shocks when investment is used as the transition variable. The results are nevertheless somewhat sensitive to different shock magnitudes. In addition, responses to a fiscal impulse depend on whether the shock is positive or negative and whether it follows periods of fiscal expansions or contractions. Current account responses to a positive fiscal shock were found to be much stronger over a two-quarter period following the shock when conditioned on periods of fiscal expansion (rising government consumption) than retrenchment. Responses to negative fiscal shocks are comparable in magnitude across conditioning histories. The importance of conditioning history and the magnitude of shocks in the current account’s response to shocks is confirmed through forecast error variance decomposition analysis.

The sensitivity of the current account responses to fiscal impulses on conditioning histories has important policy implications. The empirical finding suggests that a positive fiscal impulse, such as counter-cyclical discretionary action, would result in a deterioration of the current account balance in the short run only if it followed periods of fiscal expansion, in which government consumption had been rising. Agents would probably perceive the positive shock as long-lasting, because it would follow a rising trend in government consumption, and spend, which would reduce national savings for the same level of investment. Nevertheless, a positive fiscal shock would elicit a different current account response if it followed periods of fiscal retrenchment. Agents might perceive this shock as temporary and save it, thus offsetting the fiscal impulse and leaving national saving unchanged for the same level of investment. The finding that a stronger fiscal shock may lead to an improvement in the current account balance suggests that agents might perceive the policy impulse as unsustainable, which would prompt them to save over and above the corresponding increase in government dissaving.

Table 5. **Forecast error variance decomposition: Symmetric model**

Horizon	Std Error	*CA*	Δ*Y*	Δ*I*	Δ*G*
0	1.382	100.000	0.000	0.000	0.000
1	1.461	89.548	6.110	3.893	0.449
2	1.532	82.433	6.180	10.761	0.626
3	1.551	81.169	7.125	10.504	1.201
4	1.561	80.183	8.094	10.413	1.310
5	1.563	80.008	8.175	10.465	1.352
6	1.567	79.636	8.569	10.448	1.348
7	1.569	79.452	8.624	10.567	1.357
8	1.570	79.362	8.721	10.561	1.356
9	1.571	79.243	8.791	10.606	1.360
10	1.571	79.220	8.818	10.603	1.360
11	1.572	79.148	8.867	10.624	1.361
12	1.572	79.143	8.872	10.624	1.361

Source: Authors' estimations.

Table 6. **Forecast error variance decomposition:** $(\omega_{t-1} : \Delta I_{t-1} > 0)$ **and** $s_{t-d} = \Delta I_{t-1}$

One standard-deviation shocks

Horizon	Std Error	*CA*	Δ*Y*	Δ*I*	Δ*G*
			Positive shocks		
0	1.281	100.000	0.000	0.000	0.000
1	1.297	97.597	1.732	0.015	0.657
2	1.394	87.861	2.016	9.218	0.904
3	1.411	87.054	2.840	8.998	1.108
4	1.420	86.087	3.832	8.886	1.196
5	1.422	86.079	3.829	8.888	1.205
6	1.425	85.716	4.157	8.925	1.202
7	1.427	85.544	4.193	9.052	1.211
8	1.428	85.450	4.284	9.057	1.210
9	1.429	85.349	4.344	9.094	1.214
10	1.429	85.317	4.376	9.093	1.213
11	1.429	85.252	4.418	9.116	1.215
12	1.430	85.244	4.427	9.115	1.214
			Negative shocks		
0	1.484	100.000	0.000	0.000	0.000
1	1.498	98.170	1.209	0.055	0.566
2	1.581	90.384	1.232	7.457	0.927
3	1.588	89.740	1.768	7.394	1.098
4	1.598	88.673	2.840	7.306	1.181
5	1.599	88.606	2.860	7.336	1.198
6	1.602	88.316	3.118	7.368	1.197
7	1.603	88.166	3.161	7.468	1.205
8	1.604	88.077	3.248	7.471	1.204
9	1.605	87.967	3.325	7.501	1.208
10	1.605	87.945	3.346	7.501	1.207
11	1.606	87.876	3.397	7.519	1.209
12	1.606	87.870	3.403	7.518	1.209

Source: Authors' estimations.

Table 7. **Forecast error variance decomposition:** $(\omega_{t-1} : \Delta I_{t-1} < 0)$ **and** $s_{t-d} = \Delta I_{t-1}$

One standard-deviation shocks

Horizon	Std Error	CA	ΔY	ΔI	ΔG
		Positive shocks			
0	1.281	100.000	0.000	0.000	0.000
1	1.296	97.719	1.617	0.007	0.658
2	1.401	87.944	1.738	9.343	0.974
3	1.417	87.148	2.559	9.127	1.167
4	1.427	86.108	3.638	9.001	1.253
5	1.430	86.101	3.635	9.002	1.262
6	1.433	85.747	3.958	9.035	1.260
7	1.434	85.575	3.997	9.161	1.268
8	1.435	85.477	4.090	9.165	1.267
9	1.436	85.375	4.152	9.202	1.271
10	1.436	85.344	4.184	9.201	1.270
11	1.437	85.278	4.227	9.223	1.272
12	1.437	85.270	4.236	9.223	1.272
		Negative shocks			
0	1.484	100.000	0.000	0.000	0.000
1	1.496	98.515	0.915	0.003	0.568
2	1.579	90.765	0.874	7.357	1.004
3	1.585	90.173	1.353	7.302	1.172
4	1.595	89.083	2.442	7.214	1.261
5	1.596	89.024	2.459	7.239	1.278
6	1.599	88.715	2.743	7.266	1.277
7	1.600	88.560	2.792	7.364	1.284
8	1.601	88.462	2.888	7.366	1.283
9	1.602	88.353	2.966	7.394	1.287
10	1.602	88.329	2.989	7.395	1.287
11	1.603	88.259	3.042	7.411	1.288
12	1.603	88.253	3.048	7.411	1.288

Source: Authors' estimations.

Table 8. **Forecast error variance decomposition:** $(\omega_{t-1} : \Delta G_{t-1} > 0)$ **and** $s_{t-d} = \Delta G_{t-1}$

One standard-deviation shocks

Horizon	Std Error	CA	ΔY	ΔI	ΔG
			Positive shocks		
0	1.241	100.000	0.000	0.000	0.000
1	1.402	78.464	13.036	5.739	2.761
2	1.481	71.287	12.021	14.207	2.484
3	1.500	70.543	12.015	13.905	3.537
4	1.505	70.095	12.334	13.881	3.690
5	1.508	69.921	12.459	13.923	3.697
6	1.511	69.681	12.754	13.881	3.684
7	1.512	69.549	12.778	13.986	3.687
8	1.513	69.486	12.851	13.975	3.688
9	1.514	69.418	12.879	14.015	3.688
10	1.514	69.403	12.896	14.012	3.690
11	1.514	69.366	12.920	14.024	3.689
12	1.514	69.362	12.923	14.024	3.691
			Negative shocks		
0	1.524	100.000	0.000	0.000	0.000
1	1.610	89.627	7.272	2.056	1.045
2	1.667	84.049	7.187	7.784	0.980
3	1.684	83.147	7.544	7.628	1.681
4	1.688	82.741	7.919	7.602	1.738
5	1.690	82.581	8.028	7.647	1.744
6	1.692	82.367	8.256	7.637	1.739
7	1.693	82.254	8.286	7.718	1.742
8	1.694	82.207	8.334	7.717	1.742
9	1.694	82.143	8.369	7.745	1.743
10	1.694	82.133	8.379	7.744	1.744
11	1.695	82.097	8.405	7.755	1.743
12	1.695	82.095	8.406	7.755	1.744

Source: Authors' estimations.

Table 9. **Forecast error variance decomposition:** $(\omega_{t-1} : \Delta G_{t-1} < 0)$ **and** $s_{t-d} = \Delta G_{t-1}$

One standard-deviation shocks

Horizon	Std Error	CA	ΔY	ΔI	ΔG
Positive shock					
0	1.241	100.000	0.000	0.000	0.000
1	1.373	83.166	6.866	9.962	0.006
2	1.448	76.304	6.661	17.027	0.009
3	1.457	75.506	7.205	17.236	0.053
4	1.464	74.958	7.725	17.254	0.062
5	1.466	74.792	7.834	17.282	0.093
6	1.469	74.563	8.115	17.228	0.093
7	1.470	74.390	8.159	17.354	0.098
8	1.471	74.340	8.218	17.344	0.098
9	1.472	74.256	8.255	17.391	0.099
10	1.472	74.245	8.266	17.390	0.099
11	1.473	74.201	8.297	17.402	0.099
12	1.473	74.196	8.299	17.406	0.099
Negative shocks					
0	1.524	100.000	0.000	0.000	0.000
1	1.587	92.757	4.688	1.260	1.296
2	1.649	86.093	4.862	7.844	1.201
3	1.682	84.797	5.628	7.573	2.002
4	1.687	84.272	6.162	7.525	2.041
5	1.689	84.117	6.258	7.567	2.057
6	1.691	83.928	6.450	7.570	2.053
7	1.692	83.800	6.495	7.652	2.053
8	1.693	83.759	6.531	7.657	2.053
9	1.693	83.692	6.573	7.682	2.053
10	1.693	83.685	6.578	7.682	2.054
11	1.694	83.646	6.607	7.694	2.054
12	1.694	83.645	6.607	7.693	2.054

Source: Authors' estimations.

Table 10. **Forecast error variance decomposition:** $(\omega_{t-1} : \Delta I_{t-1} > 0)$ **and** $s_{t-d} = \Delta I_{t-1}$

Two standard-deviation shocks

Horizon	Std Error	CA	ΔY	ΔI	ΔG
Positive shocks					
0	2.663	100.000	0.000	0.000	0.000
1	2.687	98.298	1.031	0.037	0.635
2	2.882	89.058	1.098	8.843	1.002
3	2.908	88.313	1.765	8.686	1.235
4	2.932	87.018	3.074	8.549	1.359
5	2.936	86.996	3.081	8.549	1.374
6	2.943	86.551	3.455	8.622	1.372
7	2.946	86.379	3.504	8.736	1.382
8	2.948	86.261	3.613	8.746	1.380
9	2.950	86.155	3.682	8.778	1.385
10	2.951	86.112	3.724	8.779	1.384
11	2.952	86.044	3.772	8.799	1.386
12	2.952	86.034	3.782	8.798	1.386
Negative shocks					
0	2.866	100.000	0.000	0.000	0.000
1	3.059	87.802	5.036	6.637	0.525
2	3.221	81.266	5.144	12.697	0.892
3	3.245	80.382	5.984	12.603	1.031
4	3.269	79.200	7.238	12.435	1.127
5	3.273	79.117	7.224	12.512	1.147
6	3.279	78.833	7.530	12.490	1.147
7	3.282	78.702	7.548	12.595	1.155
8	3.284	78.606	7.652	12.588	1.154
9	3.286	78.518	7.699	12.625	1.158
10	3.286	78.487	7.736	12.620	1.157
11	3.287	78.432	7.773	12.636	1.159
12	3.288	78.422	7.785	12.634	1.159

Source: Authors' estimations.

Table 11. **Forecast error variance decomposition:** $(\omega_{t-1} : \Delta I_{t-1} < 0)$ **and** $s_{t-d} = \Delta I_{t-1}$

Two standard-deviation shocks

Horizon	Std Error	CA	ΔY	ΔI	ΔG
Positive shocks					
0	2.663	100.000	0.000	0.000	0.000
1	2.687	98.307	1.016	0.042	0.635
2	2.889	89.115	0.978	8.871	1.035
3	2.915	88.384	1.643	8.718	1.255
4	2.939	87.068	2.978	8.576	1.378
5	2.943	87.047	2.983	8.577	1.393
6	2.951	86.604	3.359	8.646	1.391
7	2.954	86.430	3.411	8.759	1.400
8	2.956	86.308	3.524	8.769	1.399
9	2.958	86.201	3.595	8.801	1.403
10	2.958	86.158	3.637	8.802	1.403
11	2.960	86.089	3.686	8.821	1.404
12	2.960	86.079	3.696	8.821	1.404
Negative shocks					
0	2.866	100.000	0.000	0.000	0.000
1	3.005	91.033	3.917	4.506	0.544
2	3.173	84.031	3.911	11.093	0.965
3	3.195	83.205	4.694	10.996	1.105
4	3.220	81.930	6.026	10.838	1.207
5	3.224	81.853	6.015	10.904	1.227
6	3.230	81.543	6.337	10.893	1.227
7	3.233	81.402	6.364	10.998	1.235
8	3.235	81.295	6.477	10.993	1.234
9	3.237	81.201	6.531	11.030	1.238
10	3.237	81.167	6.569	11.026	1.238
11	3.239	81.108	6.610	11.043	1.239
12	3.239	81.097	6.621	11.042	1.239

Source: Authors' estimations.

Table 12. **Forecast error variance decomposition:** $(\omega_{t-1} : \Delta G_{t-1} > 0)$ **and** $s_{t-d} = \Delta G_{t-1}$

Two standard-deviation shocks

Horizon	Std Error	CA	ΔY	ΔI	ΔG
Positive shocks					
0	2.623	100.000	0.000	0.000	0.000
1	2.810	87.204	8.014	4.558	0.224
2	2.965	79.250	7.759	12.757	0.234
3	2.999	78.504	8.459	12.507	0.530
4	3.011	77.887	9.098	12.466	0.550
5	3.017	77.646	9.234	12.513	0.607
6	3.023	77.368	9.547	12.478	0.608
7	3.026	77.193	9.604	12.584	0.618
8	3.027	77.136	9.671	12.576	0.618
9	3.029	77.038	9.724	12.618	0.620
10	3.029	77.027	9.736	12.616	0.620
11	3.030	76.975	9.774	12.631	0.620
12	3.030	76.972	9.775	12.632	0.620
Negative shocks					
0	2.907	100.000	0.000	0.000	0.000
1	3.086	88.733	7.623	2.781	0.863
2	3.215	82.216	7.565	9.415	0.804
3	3.254	81.101	8.130	9.191	1.579
4	3.265	80.570	8.590	9.146	1.694
5	3.271	80.334	8.768	9.183	1.715
6	3.276	80.070	9.055	9.165	1.709
7	3.279	79.922	9.094	9.264	1.720
8	3.280	79.868	9.152	9.260	1.720
9	3.282	79.780	9.201	9.295	1.724
10	3.282	79.769	9.212	9.294	1.725
11	3.283	79.722	9.245	9.307	1.725
12	3.283	79.720	9.246	9.308	1.726

Source: Authors' estimations.

Table 13. **Forecast error variance decomposition:** $(\omega_{t-1} : \Delta G_{t-1} < 0)$ **and** $s_{t-d} = \Delta G_{t-1}$

Two standard-deviation shocks

Horizon	Std Error	CA	ΔY	ΔI	ΔG
			Positive shocks		
0	2.623	100.000	0.000	0.000	0.000
1	2.770	90.129	2.399	6.992	0.480
2	2.931	81.684	3.127	14.417	0.771
3	2.974	79.856	5.264	14.131	0.750
4	2.992	78.945	6.243	14.071	0.741
5	2.997	78.712	6.390	14.107	0.790
6	3.002	78.497	6.627	14.075	0.801
7	3.006	78.286	6.721	14.189	0.804
8	3.006	78.256	6.753	14.184	0.808
9	3.009	78.143	6.822	14.228	0.807
10	3.009	78.139	6.825	14.228	0.808
11	3.010	78.083	6.866	14.242	0.808
12	3.010	78.080	6.866	14.245	0.808
			Negative shocks		
0	2.907	100.000	0.000	0.000	0.000
1	3.115	87.110	7.950	3.028	1.912
2	3.241	80.803	7.750	9.678	1.769
3	3.294	79.465	8.020	9.375	3.140
4	3.305	78.945	8.482	9.322	3.251
5	3.310	78.755	8.592	9.356	3.296
6	3.315	78.506	8.869	9.339	3.286
7	3.318	78.355	8.910	9.442	3.293
8	3.320	78.289	8.979	9.437	3.295
9	3.321	78.207	9.024	9.471	3.298
10	3.322	78.191	9.039	9.469	3.301
11	3.323	78.145	9.072	9.482	3.301
12	3.323	78.141	9.074	9.482	3.303

Source: Authors' estimations.

Bibliography

Algieri, B. and T. Bracke (2007), “Patterns of Current Account Adjustment – Insights from Past Experience”, *CESifo Working Paper*, No. 2029, CESifo, Munich.

Arghyrou, M.G. and G. Chortareas (2008), “Current Account Imbalances and Real Exchange Rates in the Euro Area”, *Review of International Economics*, Vol. 9, pp. 747-64.

Bai, J. and P. Perron (1998), “Estimating and Testing Linear Models with Multiple Structural Changes”, *Econometrica*, Vol. 66, No. 1, pp. 47-78.

Bai, J. and P. Perron (2003), “Computation and Analysis of Multiple Structural Change Models”, *Journal of Applied Econometrics*, Vol. 18, No. 1, pp. 1-22.

Camacho, M. (2004), “Vector Smooth Transition Regression Models for US GDP and the Composite Index of Leading Indicators”, *Journal of Forecasting*, Vol. 23, No. 3, pp. 173-96.

Chortareas, G.E., G. Kapetanios and M. Uctum (2004), “An Investigation of Current Account Solvency in Latin America Using Non Linear Nonstationarity Tests”, *Studies in Nonlinear Dynamics and Econometrics*, Vol. 8, pp. 1-17.

Clarida, R., M. Gorretti and M.P. Taylor (2006), “Are there Thresholds of Current Account Adjustment?” in R. Clarida (ed.), *Current Account Imbalances: Sustainability and Adjustment*, Chicago University Press, Chicago, IL.

Eichengreen, B. and M. Adalet (2005), “Current Account Reversals: Always a Problem?”, *NBER Working Paper*, No. 11634, National Bureau of Economic Research, Cambridge, MA.

Eitrheim, O. and T. Teräsvirta (1996), “Testing the Adequacy of Smooth Transition Autoregressive Models”, *Journal of Econometrics*, Vol. 74, No. 1, pp. 59-75.

Freund, C. (2005), “Current Account Adjustment in Industrial Countries”, *Journal of International Money and Finance*, Vol. 24, pp. 1278-98.

Freund, C. and F. Warnock (2005). “Current Account Deficits in Industrial Countries: The Bigger They Are, The Harder They Fall?”, in R. Clarida (ed.), *G7 Current Account Imbalances: Sustainability and Adjustment*, University of Chicago Press, Chicago, IL.

Ghosh, A. (1995), “International Capital Mobility amongst the Major Industrialised Countries: Too little or Too Much”, *The Economic Journal*, Vol. 105, No. 428, pp. 107-28.

Ghosh, A. and J. Ostry (1995), “The Current Account in Developing Countries: A Perspective from the Consumption-Smoothing Approach”, *World Bank Economic Review*, Vol. 9, pp. 305-33.

Glick, R. and K.S. Rogoff (1995), “Global versus Country-Specific Productivity Shocks and the Current Account”, *Journal of Monetary Economics*, Vol. 35, No. 1, pp. 159 92.

Granger, C.W. and T. Teräsvirta (1993), *Modeling Nonlinear Economic Relationships*. New York: Oxford University Press.

Huang, Y., C.R. Chen and M. Camacho (2008), "Determinants of Japanese Yen Interest Rate Swap Spreads: Evidence from a Smooth Transition Vector Autoregressive Model", *Journal of Futures Markets*, Vol. 28, No. 1, pp. 82-107.

Hussein, K.A. and L. de Mello (1999), "International Capital Mobility in Developing Countries: Theory and Evidence", *Journal of International Money and Finance*, Vol. 18, No. 3, pp. 367-81.

Kapetanios, G., Y. Shin and A. Snell (2003), "Testing for Unit Root in the Nonlinear STAR Framework", *Journal of Econometrics*, Vol. 112, pp. 359-79.

Koop, G., M.H. Pesaran and S.M. Potter (1996), "Impulse Response Analysis in Nonlinear Multivariate Models", *Journal of Econometrics*, Vol. 74, No. 1, pp. 119-47.

Luukkonen, R., P. Saikkonen and T. Teräsvirta (1988), "Testing Linearity Against Smooth Transition Autoregressive Models", *Biometrika*, Vol. 75, No. 3, pp. 491-9.

Milesi-Ferretti, G.M. and A. Razin (1998), "Sharp Reductions in Current Account Deficits: An Empirical Investigation", *European Economic Review*, Vol. 42, No. 3-5, pp. 897-908.

Ng, S. and P. Perron (2001), "Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power", *Econometrica*, Vol. 69, No. 6, pp. 1519-1554.

Perron, P. and Z. Qu (2007), "A Simple Modification to Improve the Finite Sample Properties of Ng and Perron's Unit Root Tests", *Economics Letters*, Vol. 94, No. 1, pp. 12-19.

Saikkonen, P. and R. Luukkonen (1988), "Lagrange Multiplier Tests for Testing Non-linearities in Time Series Models", *Scandinavian Journal of Statistics*, Vol. 15, No. 1, pp. 55-68.

Teräsvirta, T. (1994), "Specification, Estimation and Evaluation of Smooth Transition Autoregressive Models", *Journal of the American Statistical Association*, Vol. 89, pp. 208-18.

Teräsvirta, T. and H.M. Anderson (1992), "Characterizing Nonlinearities in Business Cycles Using Smooth Transition Autoregressive Models", *Journal of Applied Econometrics*, Vol. 7, pp. S119-S136.

Tsay, R.S. (1986), "Nonlinearity Tests for Time Series", *Biometrika*, Vol. 73, No. 2, pp. 461-6.

Weise, C.L. (1999), "The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autoregression Approach", *Journal of Money, Credit and Banking*, Vol. 31, No. 1, pp. 85-108.

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